



Artificial Intelligence in Healthcare: A Systematic Review of Diagnostic, Predictive, and Decision-Support Applications

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ABSTRACT

Artificial intelligence (AI) is increasingly transforming healthcare by enabling advanced approaches to disease diagnosis, clinical prediction, and decision support. This systematic review examines the applications, benefits, challenges, and emerging directions of AI in healthcare, with particular emphasis on diagnostic systems, predictive analytics, and clinical decision-support applications. Relevant peer-reviewed studies were systematically identified, screened, and synthesized to examine how machine learning, deep learning, natural language processing, and related AI techniques are being integrated into clinical practice. The findings indicate that AI-based diagnostic applications have demonstrated substantial potential in medical imaging, pathology, disease detection, and clinical classification by improving pattern recognition, diagnostic accuracy, and the efficiency of healthcare workflows. Predictive applications have increasingly supported risk stratification, early identification of disease deterioration, hospital readmission prediction, mortality estimation, and personalized treatment planning. AI-enabled decision-support systems have also assisted clinicians by integrating large and heterogeneous datasets to generate risk estimates, treatment recommendations, and clinically relevant alerts. However, the review identifies persistent challenges related to data quality, algorithmic bias, interpretability, patient privacy, cybersecurity, interoperability, regulatory oversight, and the generalizability of AI models across healthcare settings and populations. Overall, the evidence suggests that AI can complement rather than replace clinical expertise when appropriately validated, transparently implemented, and integrated into existing healthcare systems. Future research should prioritize prospective clinical validation, explainable and trustworthy AI, equitable datasets, human-AI collaboration, and robust governance frameworks to support safe, effective, and patient-centred adoption of AI in healthcare.

1. Introduction

Artificial intelligence (AI) has emerged as one of the most consequential technological developments in contemporary healthcare, transforming how clinical information is generated, interpreted, and translated into decisions. The rapid expansion of electronic health records, medical imaging repositories, genomic datasets, wearable devices, laboratory information systems, and other digital health technologies has created large and increasingly complex datasets that exceed the capacity of conventional analytical approaches. AI encompasses a broad range of computational techniques, including machine learning, deep learning, natural language processing, computer vision, and knowledge-based systems, which can identify patterns within complex data and support tasks traditionally requiring substantial human expertise. In healthcare, these capabilities have stimulated applications ranging from automated interpretation of medical images and clinical prediction to personalized treatment recommendations and decision support. Consequently, AI is increasingly being investigated not merely as a technological innovation but as an instrument for improving diagnostic accuracy, anticipating clinical outcomes, optimizing resource utilization, and supporting evidence-informed clinical practice.

Diagnostic applications represent one of the most extensively studied areas of healthcare AI. Medical diagnosis frequently involves the integration of heterogeneous information, including symptoms, clinical histories, laboratory findings, physiological measurements, and imaging results. Machine learning and deep learning algorithms can process such information to identify patterns associated with diseases or clinically significant abnormalities. In radiology, for example, convolutional neural networks and other computer-vision approaches have been investigated for the detection and classification of abnormalities in X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and mammography. Similar approaches have been applied in pathology for the analysis of digitized tissue specimens and in ophthalmology for the detection of retinal and other ocular diseases. AI-assisted diagnostic systems may provide rapid preliminary assessments, prioritize cases according to clinical urgency, and potentially improve consistency in settings where specialist expertise is limited (Ogayemi, 2026). Nevertheless, diagnostic performance reported under controlled research conditions does not necessarily translate directly into clinical effectiveness, making external validation, generalizability, interpretability, and integration into clinical workflows important considerations.

Beyond diagnosis, AI has increasingly been applied to predictive healthcare, where the objective is to estimate the probability of future clinical events and identify patients who may require early intervention. Predictive models have been developed for outcomes such as hospital readmission, mortality, disease progression, treatment response, complications, and deterioration among hospitalized patients. Algorithms including logistic regression, random forests, support vector machines, gradient-boosting methods, and neural networks have been evaluated across diverse clinical populations and data sources. In intensive care and emergency medicine, predictive systems can analyze continuously updated clinical information to identify patients at elevated risk of deterioration. In chronic disease management, AI-based models have been explored for predicting conditions such as cardiovascular disease, diabetes-related complications, and kidney disease. The potential value of these systems lies in shifting healthcare from predominantly reactive models toward more anticipatory approaches in which risk can be recognized earlier and clinical resources can be directed toward patients most likely to benefit.

A further dimension of AI in healthcare involves clinical decision support. While diagnostic systems primarily seek to identify diseases and predictive systems estimate future risks, decision-support applications seek to assist healthcare professionals in selecting or prioritizing appropriate clinical actions. AI-based decision-support systems may synthesize patient-specific information with clinical guidelines, historical outcomes, medical literature, and other sources of evidence to support treatment selection, risk stratification, medication management, triage, and care planning. Natural language processing has also expanded the potential of AI by enabling the extraction and interpretation of clinically relevant information from unstructured clinical notes and medical records. More recently, generative AI and large language models have introduced additional possibilities for clinical information retrieval, documentation, communication, and decision-support workflows. However, these systems also raise concerns regarding inaccurate outputs, automation bias, explainability, accountability, privacy, and the appropriate division of responsibility between healthcare professionals and AI systems.

Despite substantial progress, the adoption of AI in healthcare remains accompanied by important technical, clinical, ethical, and organizational challenges. AI models can perform differently across hospitals, geographical regions, demographic groups, and healthcare systems because of differences in patient populations, data quality, clinical practices, equipment, and disease prevalence. Bias in training datasets can consequently contribute to unequal performance across population groups, raising concerns about fairness and health equity. Data privacy and security are also critical because AI development frequently requires access to highly sensitive medical information. Furthermore, many high-performing models operate as relatively opaque systems, making it difficult for clinicians and patients to understand how particular predictions or recommendations are generated. The lack of transparency may reduce trust and complicate accountability when AI-supported decisions contribute to adverse outcomes. Regulatory uncertainty, interoperability limitations, inadequate infrastructure, workforce training requirements, and resistance to workflow changes may further constrain implementation.

The expanding evidence base therefore requires systematic examination rather than an exclusive focus on algorithmic performance. Individual studies often concentrate on particular diseases, datasets, algorithms, or clinical settings, making it difficult to understand the broader trajectory of AI applications across healthcare. A systematic synthesis can clarify how AI is being used across diagnostic, predictive, and decision-support domains, identify recurring benefits and limitations, and distinguish technological promise from evidence of practical clinical value (Al-Nafjan, 2025). Such an approach is particularly important because high predictive accuracy alone does not establish that an AI system improves patient outcomes, reduces healthcare disparities, enhances clinician decision-making, or provides cost-effective care. Evaluation of clinical utility, generalizability, human-AI interaction, implementation feasibility, and ethical implications is therefore essential alongside conventional measures of model performance.

Against this background, this systematic review examines the application of artificial intelligence in healthcare, with particular emphasis on diagnostic, predictive, and clinical decision-support applications. The review synthesizes evidence concerning the principal AI techniques and healthcare contexts in which they have been employed, their reported contributions to diagnostic and predictive performance, and their potential role in supporting clinical decision-making. It also examines the major limitations and implementation challenges associated with AI-enabled healthcare, including data quality, algorithmic bias, interpretability, privacy, validation, interoperability, and clinical integration. By bringing these dimensions together, the review seeks to provide an integrated understanding of the current evidence on AI in healthcare and to identify areas requiring further research to support safe, equitable, clinically meaningful, and responsible adoption of AI technologies.

2. Methodology

2.1 Research Design

This study employed a systematic literature review design to synthesize existing evidence on the applications of artificial intelligence (AI) in healthcare, with particular emphasis on diagnostic applications, predictive analytics, and clinical decision-support systems. A systematic review approach was selected because AI in healthcare encompasses a rapidly expanding and multidisciplinary body of research spanning medicine, computer science, biomedical engineering, public health, nursing, and health informatics. The review was designed to identify major application areas, examine reported benefits and clinical contributions, evaluate methodological and technological trends, and synthesize the principal challenges associated with the implementation of AI-based healthcare technologies. The review process was structured around the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to promote transparency, reproducibility, and methodological rigor.

2.2 Review Objectives and Research Questions

The review was guided by the overall objective of examining how AI technologies are being applied to diagnosis, prediction, and clinical decision-making in healthcare. Specifically, the review sought to determine the principal diagnostic applications of AI across medical specialties, examine the use of AI and machine learning for predicting clinical outcomes and risks, assess the contribution of AI-based decision-support systems to clinical practice, and identify the principal technical, ethical, organizational, and clinical barriers affecting the adoption of these technologies. Accordingly, the review addressed the following questions: What are the major diagnostic applications of AI in healthcare? How are AI technologies being used to predict diseases, complications, and patient outcomes? How do AI-based systems support clinical decision-making? What benefits and limitations are reported in the literature? What ethical, technical, regulatory, and implementation challenges influence the safe and effective use of AI in healthcare?

2.3 Search Strategy

A comprehensive literature search was conducted across major electronic scholarly databases to identify peer-reviewed studies relevant to AI applications in healthcare. The search strategy incorporated multidisciplinary databases and indexing services covering medical, technological, and health-science literature. Search terms were developed around the principal concepts of artificial intelligence, healthcare, diagnosis, prediction, and clinical decision support. Combinations of keywords and Boolean operators were used, including terms such as "artificial intelligence," "AI," "machine learning," "deep learning," "neural networks," "healthcare," "medicine," "medical diagnosis," "clinical prediction," "risk prediction," "prognosis," "clinical decision support," and "decision-support systems." Synonyms and related terminology were combined using the operators "AND" and "OR" to broaden retrieval while maintaining conceptual relevance. Reference lists of particularly relevant studies were also examined to identify additional publications that may not have been retrieved through the electronic database searches.

2.4 Eligibility Criteria

Studies were considered eligible when they examined the application, evaluation, implementation, or implications of AI technologies within healthcare settings. The review included studies addressing AI-supported medical diagnosis, disease detection, image interpretation, clinical prediction, risk stratification, prognosis, patient monitoring, treatment recommendation, and clinical decision support. Studies examining machine learning, deep learning, natural language processing, computer vision, neural networks, and other computational approaches were considered where these technologies were applied to healthcare-related problems. Peer-reviewed empirical studies, systematic reviews, evidence syntheses, and other academically rigorous publications that provided substantive evidence concerning AI in healthcare were considered. Publications were excluded when they focused exclusively on theoretical AI development without a healthcare application, addressed non-healthcare applications, lacked sufficient methodological or conceptual information, or were duplicated across databases. Non-scholarly materials and publications that did not provide sufficient evidence relevant to the review objectives were also excluded.

2.5 Study Selection Process

The study-selection process was conducted in several stages. Initially, all records retrieved from the selected databases were compiled and duplicates were removed. Titles and abstracts were subsequently screened against the predefined eligibility criteria. Studies considered potentially relevant underwent full-text assessment to determine whether they satisfied the inclusion requirements and directly addressed one or more of the review questions. During full-text screening, particular attention was given to the AI technology examined, healthcare application, clinical context, outcomes assessed, and relevance to diagnosis, prediction, or decision support. Studies that did not meet the eligibility criteria at this stage were excluded, with the principal reasons for exclusion documented. The final set of eligible publications constituted the evidence base for the systematic synthesis.

2.6 Data Extraction

A structured data-extraction framework was used to organize information from the studies included in the review. Extracted information comprised publication characteristics, study objectives, healthcare setting, clinical specialty, patient or population characteristics where reported, AI technique, data type, application area, comparator or conventional approach, principal outcomes, and major findings. Additional information concerning diagnostic accuracy, predictive performance, clinical utility, decision-support capabilities, implementation conditions, and reported limitations was extracted where available. Information relating to ethical concerns, explainability, data privacy, algorithmic bias, interoperability, regulatory issues, and clinician acceptance was also recorded because these factors are important in determining whether technically successful AI systems can be translated into routine healthcare practice.

2.7 Quality Assessment

The methodological quality and relevance of the included literature were assessed using criteria appropriate to the design of individual studies. Particular attention was given to the clarity of research objectives, appropriateness of study design, adequacy of data sources, transparency of AI model development, validity of evaluation procedures, appropriateness of performance measures, and clarity of reported findings. For AI diagnostic and predictive studies, consideration was given to issues such as training and validation procedures, independent testing, external validation, sample characteristics, potential data leakage, class imbalance, and reporting of performance metrics. Studies with important methodological limitations were not necessarily excluded when they provided relevant evidence; instead, their limitations were considered during interpretation and synthesis. This approach enabled the review to distinguish between promising experimental findings and evidence demonstrating stronger potential for clinical applicability.

2.8 Data Synthesis and Analysis

Because the included literature was expected to demonstrate substantial heterogeneity in AI techniques, healthcare settings, datasets, clinical outcomes, and evaluation methods, a narrative and thematic synthesis approach was adopted. Quantitative findings were compared descriptively where studies reported comparable performance measures, while differences in datasets, populations, clinical tasks, and validation strategies were considered when interpreting reported results. The findings were organized into three principal domains: diagnostic applications, predictive applications, and clinical decision-support applications. Within these domains, recurring themes concerning accuracy, efficiency, early detection, risk stratification, personalization of care, workflow support, and clinical decision-making were identified and synthesized. A separate thematic analysis was undertaken to examine cross-cutting challenges, including data quality, algorithmic bias, interpretability, privacy and security, interoperability, regulatory uncertainty, clinical validation, and barriers to implementation. This synthesis was intended to identify broader patterns in the evidence rather than treat individual model-performance results as directly comparable across fundamentally different clinical tasks.

2.9 Management of Heterogeneity

Heterogeneity was explicitly considered because AI healthcare research varies considerably in terms of algorithms, datasets, clinical populations, disease categories, healthcare systems, and outcome measures. Rather than combining heterogeneous performance estimates into a single numerical effect size, the review compared findings according to application category and methodological context. Diagnostic studies were considered in relation to tasks such as medical-image interpretation, disease detection, and clinical classification, whereas predictive studies were examined according to risk prediction, prognosis, disease progression, and patient-outcome forecasting. Decision-support studies were analyzed according to their role in assisting clinicians with diagnosis, treatment selection, monitoring, triage, and care planning. This approach allowed the review to preserve important contextual differences and avoid misleading comparisons between AI systems developed for substantially different purposes.

2.10 Reporting and Transparency

The review findings were reported in accordance with systematic-review reporting principles, with the search and selection process presented transparently and the characteristics of the included evidence described systematically. The review distinguished between evidence demonstrating technical performance and evidence supporting real-world clinical effectiveness or implementation. Particular consideration was given to whether AI systems had undergone external validation, prospective evaluation, integration into clinical workflows, or assessment of their effects on patient and healthcare outcomes. The methodology was structured to ensure that conclusions were based on the collective evidence rather than isolated claims concerning individual AI models. Through this approach, the review provides a comprehensive synthesis of the current evidence concerning the role of artificial intelligence in healthcare diagnosis, prediction, and clinical decision support.

3. Findings and Discussion

3.1 Diagnostic Applications of Artificial Intelligence in Healthcare

The reviewed literature demonstrates that diagnostic applications represent one of the most extensively investigated areas of artificial intelligence (AI) in healthcare. Machine learning (ML), deep learning (DL), convolutional neural networks (CNNs), natural language processing (NLP), and increasingly multimodal foundation models have been applied to identify diseases, classify clinical abnormalities, segment anatomical structures, and extract diagnostically relevant information from large and heterogeneous datasets. Across the literature, AI systems frequently demonstrate high discriminatory performance under controlled research conditions, particularly in image-based diagnosis. However, the findings also indicate that reported accuracy does not necessarily translate directly into superior clinical outcomes because performance can be affected by dataset composition, disease prevalence, image quality, population differences, workflow integration, and external validation. Consequently, the evidence supports AI primarily as an augmentation technology that can increase the consistency and speed of diagnostic assessment rather than as an autonomous replacement for healthcare professionals.

3.1.1 Medical Imaging and Radiological Diagnosis

Medical imaging constitutes a major domain of AI-supported diagnosis. The reviewed studies show extensive applications of deep learning to X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, mammography, retinal imaging, and other modalities. CNN-based systems have been particularly effective in image classification and lesion detection because they can learn hierarchical visual representations directly from large collections of labelled images. Applications include detecting pulmonary abnormalities on chest radiographs, identifying intracranial abnormalities on CT, classifying breast lesions on mammography, detecting diabetic retinopathy from retinal photographs, and identifying abnormalities in MRI examinations. AI has also been used for semantic and instance segmentation, enabling automated delineation of tumors, organs, vessels, and other anatomical structures (Abayomi 2024). These capabilities are clinically relevant because segmentation can support disease quantification, treatment planning, longitudinal monitoring, and surgical or radiotherapy planning.

A consistent finding across the literature is that AI can achieve diagnostic performance comparable with, and in some narrowly defined tasks sometimes exceeding, that of individual clinicians. For example, deep-learning systems for diabetic-retinopathy screening have demonstrated high sensitivity and specificity, while AI-assisted mammography and chest-imaging systems have shown potential for improving detection and reducing interpretation workload. Similar evidence has emerged from CT-based applications for pulmonary nodules, intracranial hemorrhage, stroke, and other acute abnormalities. Nevertheless, comparisons with conventional radiology should be interpreted carefully. Expert radiologists incorporate clinical history, previous examinations, imaging context, and disease probability in ways that may not be represented in a single-image benchmark. Moreover, some studies demonstrating high AI performance use retrospective datasets with carefully selected cases, which may overestimate performance in routine clinical populations.

The findings therefore suggest that the strongest practical contribution of AI in radiology is augmentation. AI can function as a second reader, prioritization mechanism, abnormality detector, or quantitative measurement tool, allowing radiologists to focus attention on complex cases. AI-based segmentation can also reduce repetitive manual tasks and improve measurement consistency. However, false-positive alerts may increase workload, while false-negative results can create risks if clinicians develop excessive confidence in automated outputs. The literature consequently emphasizes external validation, prospective evaluation, explainability, and monitoring for performance degradation after deployment. Overall, AI has demonstrated substantial diagnostic potential in medical imaging, but clinical value depends on how accurately systems perform across diverse patient populations and how effectively they are incorporated into radiological workflows.

3.1.2 Pathology, Laboratory Diagnosis, and Disease Detection

AI has also expanded diagnostic capabilities in digital pathology, microscopy, laboratory medicine, and automated disease detection. In digital pathology, deep-learning models can analyze whole-slide images to identify malignant tissue, classify tumors, recognize cellular abnormalities, and quantify histopathological features. AI-supported systems have been investigated

for breast, prostate, lung, colorectal, skin, and other cancers, as well as for grading disease severity and identifying prognostically important morphological patterns. Rather than simply reproducing visual inspection, AI can evaluate thousands or millions of image regions systematically, providing quantitative information that may be difficult to obtain consistently through manual examination.

The reviewed evidence indicates that AI-assisted pathology can produce high sensitivity and specificity for several narrowly defined classification tasks. Automated algorithms can also reduce inter-observer variability by applying consistent computational criteria to image features. This is particularly relevant where diagnosis depends on the recognition and quantification of subtle morphological differences. In microbiology and microscopy, AI has similarly been investigated for detecting parasites, bacteria, abnormal blood cells, tuberculosis-related patterns, and other clinically significant features. Laboratory AI applications extend beyond image analysis to include interpretation of biochemical, hematological, molecular, and other diagnostic data (Pasham, 2023). These systems can identify complex associations among laboratory variables and support automated flagging of abnormal results.

An important finding, however, is that diagnostic speed and reproducibility are not automatically equivalent to clinical superiority. Laboratory and pathology datasets can vary substantially according to instruments, staining procedures, sample preparation, laboratories, demographic composition, and disease spectrum. Consequently, an algorithm trained in one institution may perform differently elsewhere. Digital pathology also presents technical challenges involving extremely large image files, image standardization, annotation quality, and computational requirements. The literature therefore supports the use of AI as a complementary diagnostic mechanism, particularly for screening, case prioritization, quantitative assessment, and quality assurance, while emphasizing the continued importance of specialist interpretation for diagnostically ambiguous cases.

3.1.3 Multimodal and Early Diagnostic Systems

A major development identified in the literature is the movement from single-modality AI toward multimodal diagnostic systems. Instead of analysing an image, laboratory result, or clinical record independently, multimodal systems can integrate imaging data with electronic health records (EHRs), laboratory measurements, demographic characteristics, clinical notes, medication histories, physiological signals, and other patient information. This approach is particularly important for diseases whose diagnosis depends on the interaction of multiple clinical indicators rather than on a single observable feature.

Multimodal AI has demonstrated potential for detecting complex patterns associated with cancer, cardiovascular disease, neurological disorders, infectious diseases, and other conditions. For example, an imaging abnormality may have substantially different diagnostic significance depending on the patient's age, symptoms, laboratory results, previous diagnoses, and treatment history. Combining these sources allows AI models to approximate a more comprehensive clinical context. NLP further enables systems to extract information from unstructured clinical notes, radiology reports, pathology reports, and discharge summaries, thereby converting previously underused textual information into computable features.

The evidence suggests that multimodal systems may improve early detection because they can identify weak signals distributed across several data sources. Nevertheless, the complexity of multimodal models introduces additional challenges concerning missing data, data interoperability, temporal alignment, privacy, bias, and interpretability. The absence of one modality may also affect model performance. Thus, while multimodal AI represents an important direction for comprehensive diagnosis, evidence from real-world prospective implementation remains more limited than evidence from retrospective development studies.

3.2 Predictive Applications of Artificial Intelligence in Healthcare

The second major finding concerns the increasing use of AI for prediction rather than merely recognizing existing disease. Predictive AI models use historical and real-time clinical information to estimate the probability of future events, including disease development, clinical deterioration, complications, mortality, readmission, treatment response, and disease recurrence. Random forests, support vector machines, gradient-boosting algorithms, neural networks, recurrent neural networks, and transformer-based architectures have all been investigated for these purposes (Ouanes, 2024). The literature indicates that predictive applications can transform healthcare from a predominantly reactive model toward earlier identification of patients at elevated risk. However, predictive accuracy alone is insufficient to demonstrate clinical benefit; a useful prediction must be timely, actionable, and appropriately integrated into clinical decision-making.

3.2.1 Disease Risk Prediction and Early Warning

AI-based disease-risk prediction has been applied to cardiovascular disease, diabetes, cancer, infectious diseases, kidney disease, neurological conditions, and other chronic and acute illnesses. Models can combine demographic characteristics, laboratory measurements, vital signs, previous diagnoses, medication histories, genetic information, lifestyle factors, and longitudinal EHR data to estimate individual risk. In cardiovascular medicine, for example, ML models have been developed to identify patients at

increased risk of cardiovascular events using combinations of clinical and demographic variables. Similarly, predictive models have been investigated for diabetes onset and progression, cancer recurrence, sepsis, acute kidney injury, and deterioration among hospitalized patients.

The principal finding is that AI can identify nonlinear relationships and interactions that may be difficult to capture through conventional statistical models. This can improve risk stratification, particularly when large longitudinal datasets are available. Early-warning systems are especially relevant in hospital environments because subtle changes in vital signs, laboratory results, and clinical observations may precede clinically obvious deterioration. AI can continuously process these indicators and generate alerts before a serious event becomes apparent.

Despite this potential, the literature reveals an important distinction between discrimination and clinical utility. A model may accurately distinguish high-risk from low-risk patients without necessarily improving outcomes. Excessive alerts may contribute to alarm fatigue, whereas poorly calibrated predictions can result in inappropriate escalation or missed intervention. Therefore, calibration, sensitivity, specificity, positive predictive value, clinical utility, and prospective impact should be evaluated alongside measures such as area under the receiver operating characteristic curve. The evidence consequently supports AI-based risk prediction as a mechanism for augmenting surveillance and prioritization, provided that predictions are validated and linked to appropriate clinical responses.

3.2.2 Patient Outcomes, Mortality, and Hospital Readmission Prediction

AI has been widely investigated for predicting mortality, hospital readmission, length of stay, complications, and clinical deterioration. EHR-based models can analyse large volumes of structured and unstructured information to identify patients whose clinical trajectories indicate elevated risk. Mortality prediction has been explored across intensive care, emergency medicine, oncology, cardiovascular medicine, and general inpatient populations (Almadani, 2025). Similarly, readmission models seek to identify patients who may require additional monitoring, discharge planning, or follow-up support.

The reviewed evidence indicates that AI-based prediction can support earlier intervention and more efficient allocation of healthcare resources. For example, identification of patients at high risk of deterioration may encourage closer physiological monitoring or earlier clinical assessment. Readmission prediction can inform discharge planning and post-discharge follow-up, while length-of-stay prediction can support bed management and staffing decisions. In intensive care, continuously updated predictive models can potentially provide more dynamic assessments than static risk scores calculated at admission.

However, predictive performance varies considerably according to clinical setting, outcome definition, population, and data availability. Models developed in one hospital may lose accuracy when transferred to another institution because of differences in patient characteristics, clinical protocols, coding practices, and healthcare resources. Furthermore, socioeconomic and demographic variables can introduce inequities if models learn historical patterns of unequal access rather than clinically meaningful risk. Consequently, the literature emphasizes local validation, fairness assessment, recalibration, and continuous monitoring. The value of predictive AI therefore lies not simply in forecasting an outcome but in enabling timely and equitable interventions based on that forecast.

3.2.3 Personalized and Precision Healthcare

The reviewed literature identifies personalized and precision healthcare as an important area in which predictive AI can move beyond population-level averages toward patient-specific risk and treatment assessment. AI models can combine clinical, genetic, molecular, behavioral, lifestyle, and environmental information to characterize individual disease trajectories and predict treatment response. In oncology, for instance, AI has been investigated for predicting treatment response and recurrence using combinations of tumor characteristics, genomic information, pathology images, and clinical data. Similar approaches have been applied to pharmacogenomics, chronic disease management, and individualized risk estimation.

AI is particularly suited to precision medicine because many clinical outcomes depend on complex interactions among numerous variables. Conventional approaches often rely on a relatively small number of established predictors, whereas ML can evaluate high-dimensional datasets containing thousands of potential features. This creates opportunities for identifying patient subgroups with distinct risks or treatment responses. In chronic diseases, predictive models can also support individualized monitoring by identifying changes in patient trajectories before conventional clinical thresholds are reached.

Nevertheless, the findings indicate that personalized prediction requires careful consideration of data quality and representativeness. Genomic and clinical datasets may be disproportionately derived from particular populations, limiting generalizability to underrepresented groups. In addition, predictions based on correlations do not necessarily establish biological mechanisms or causal treatment effects. AI can therefore contribute to precision medicine by identifying patterns and estimating

individualized risks, but treatment decisions still require clinical interpretation, patient preferences, and evidence concerning treatment efficacy and safety.

3.3 AI-Based Clinical Decision-Support Applications

Beyond diagnosis and prediction, AI is increasingly being incorporated into clinical decision-support systems (CDSS). The reviewed literature indicates that AI-enabled decision support can synthesize complex information and provide recommendations concerning diagnostic investigations, treatment options, medication use, patient monitoring, and resource allocation. Unlike traditional rule-based CDSS, ML-based systems can learn relationships from large datasets and identify patterns that may not be captured by predefined rules (Hasan, 2025). The emerging evidence nevertheless indicates that effective decision support depends heavily on clinician-AI interaction, transparency, workflow compatibility, and the ability of professionals to critically evaluate automated recommendations.

3.3.1 Clinical Decision Support and Treatment Recommendations

AI-based CDSS applications include differential-diagnosis support, treatment selection, clinical guideline assistance, prognosis estimation, and recommendation of diagnostic tests. Systems can combine patient characteristics with laboratory results, imaging, previous diagnoses, medication histories, and clinical guidelines to generate potential diagnostic or therapeutic options. In oncology, for example, AI-supported systems have been investigated for matching patient and tumor characteristics with potential treatment strategies. In emergency and acute-care settings, AI can support clinicians by identifying high-risk patients and highlighting clinically relevant information within large EHR datasets.

The findings suggest that AI can reduce the cognitive burden associated with processing large quantities of information, particularly in complex clinical environments. However, the evidence does not support treating AI recommendations as inherently authoritative. Clinical recommendations generated from historical datasets may reproduce existing practice patterns, including inappropriate or outdated practices. There is also a risk of automation bias, whereby users may accept an algorithmic recommendation without sufficiently questioning its basis. Consequently, effective CDSS should present AI outputs as decision-support information, with clinicians retaining responsibility for contextual interpretation and final decisions.

3.3.2 Medication Management and Therapeutic Decision-Making

Medication management is another significant area of AI application. ML and NLP systems have been developed to identify potential drug-drug interactions, predict adverse drug reactions, support medication reconciliation, estimate treatment response, and assist with individualized therapeutic decisions. AI can analyse medication histories alongside diagnoses, laboratory measurements, demographic characteristics, and other clinical variables to identify patients who may be vulnerable to medication-related complications.

The reviewed evidence indicates that automated medication surveillance can improve the identification of potentially unsafe combinations and support more systematic monitoring. Predictive models may also help identify patients at increased risk of adverse reactions or treatment failure. In some therapeutic areas, AI has been investigated for optimizing treatment selection according to individual characteristics rather than relying exclusively on population-level recommendations. These capabilities are particularly relevant to patients receiving multiple medications or those with complex chronic conditions.

Nevertheless, medication-related AI requires a particularly high level of reliability because errors can have immediate clinical consequences. Drug databases must remain current, patient information must be accurate, and recommendations must account for contraindications, renal and hepatic function, allergies, age-related factors, and other clinical considerations. The evidence therefore supports AI as an additional safety and analytical layer rather than an independent prescribing mechanism. Pharmacists and clinicians remain essential for interpreting recommendations and considering patient-specific circumstances that may not be fully represented in available data.

3.3.3 Clinical Workflow, Triage, and Resource Allocation

The literature further demonstrates expanding applications of AI in triage, workflow optimization, appointment prioritization, emergency-care management, hospital bed allocation, and other operational activities. AI-supported triage systems can classify patients according to urgency by analysing symptoms, vital signs, medical history, and other available information. In emergency departments, predictive algorithms have been investigated for estimating admission requirements, identifying patients likely to deteriorate, and prioritizing clinical attention (Montani, 2019). AI can also support scheduling and resource allocation by predicting patient volumes, length of stay, staffing requirements, and demand for hospital resources.

A recurring finding is that workflow applications may generate benefits even when AI does not directly make a clinical diagnosis. Automating repetitive information-processing tasks can reduce administrative workload and allow professionals to devote more

time to direct patient care. Predictive scheduling can improve the utilization of beds, operating rooms, imaging equipment, and staff, while automated prioritization may help direct limited resources toward patients with greater urgency. However, improvements in operational efficiency depend on whether AI recommendations fit existing workflows. Poorly integrated systems can instead introduce additional documentation requirements, alerts, or technical burdens.

3.4 Benefits and Clinical Impact of Artificial Intelligence

3.4.1 Diagnostic Accuracy, Efficiency, and Timeliness

The reviewed evidence indicates that artificial intelligence (AI) can substantially enhance several stages of the diagnostic process, particularly where healthcare generates large volumes of structured or image-based data. Machine-learning and deep-learning systems have demonstrated the capacity to identify patterns in radiographs, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, pathology slides, electrocardiograms, and other clinical datasets that may be difficult to detect consistently through conventional approaches. The principal benefit is not necessarily the replacement of clinicians, but the augmentation of clinical interpretation through rapid pattern recognition, prioritization of abnormal examinations, and provision of additional diagnostic information. The FDA identifies image processing, early disease detection, diagnosis, prognosis, and risk assessment among important applications of AI-enabled medical technologies.

In medical imaging, AI-assisted interpretation can improve efficiency by automatically screening large numbers of examinations and identifying cases requiring urgent human review. For example, algorithms can flag suspected abnormalities on chest radiographs or CT scans, prioritize potentially critical findings, and support radiologists by drawing attention to regions of interest. Similar approaches have been investigated in pathology, ophthalmology, dermatology, cardiology, and cancer detection. The reviewed literature therefore suggests that AI has particular value where diagnostic workflows are characterized by high volumes of repetitive image or signal interpretation. However, reported improvements in algorithmic performance should not automatically be interpreted as equivalent improvements in real-world patient outcomes because many studies evaluate retrospective datasets rather than prospective clinical workflows. The FDA's continuing emphasis on real-world performance evaluation reflects this distinction between technical performance and sustained clinical effectiveness after deployment.

A further benefit is diagnostic timeliness. AI systems can process information continuously and rapidly, potentially shortening the interval between data acquisition and clinical interpretation. This is especially relevant to time-sensitive conditions in which earlier recognition can influence subsequent management. Predictive algorithms may identify patients at elevated risk before a condition becomes clinically obvious, thereby supporting earlier investigation or intervention. Nevertheless, the evidence indicates that timeliness depends on successful integration with clinical workflows (Xu, 2023). An algorithm that generates accurate predictions but is poorly integrated into electronic health records, alert systems, or clinical decision processes may provide limited practical benefit. Thus, AI-related gains in diagnostic efficiency arise from the interaction between algorithmic capability, data availability, workflow integration, and professional interpretation rather than from computational performance alone.

The findings also indicate that AI may reduce certain forms of diagnostic error while introducing other forms of risk. Human clinicians can experience fatigue, workload-related variation, and difficulty processing very large datasets, whereas automated systems can apply the same computational procedure repeatedly. Conversely, AI systems may produce systematic errors when presented with data that differ from their training populations. Consequently, the strongest evidence supports an AI-augmented diagnostic model, in which algorithms provide screening, prioritization, quantitative measurements, or second-reader functions while clinicians retain responsibility for contextual interpretation and final decisions. This approach is consistent with international guidance emphasizing that AI should strengthen healthcare capacity while maintaining appropriate human accountability and oversight.

3.4.2 Patient-Centred Care and Health Outcomes

The synthesis further indicates that AI can contribute to patient-centred healthcare by enabling more individualized assessment and continuous analysis of patient information. Predictive models can combine demographic characteristics, laboratory measurements, clinical histories, physiological signals, medication information, and other variables to estimate individual risks and support treatment planning. Rather than applying identical interventions to all patients with the same broad diagnosis, AI-supported systems can assist clinicians in identifying clinically meaningful differences among patients and selecting interventions according to individual risk profiles. The FDA similarly identifies personalized diagnostics and the identification of patterns in disease progression as important areas of AI-enabled healthcare.

Continuous monitoring represents another important patient-centred application. AI can analyze streams of information from electronic health records, bedside monitors, wearable devices, imaging examinations, and other sources to detect changes that

may warrant clinical attention. Such systems may support earlier recognition of deterioration and facilitate intervention before a patient's condition becomes more severe. In chronic disease management, AI-supported monitoring may also help identify changes in physiological measurements or treatment response between routine clinical encounters. The potential value is particularly evident where conventional care is episodic and clinicians have limited opportunity to observe patients continuously. AI may also improve treatment selection by supporting risk stratification and clinical decision-making. For example, predictive models can assist clinicians in estimating the probability of complications, identifying patients who may require closer monitoring, or distinguishing individuals according to predicted treatment response (Tun, 2025). This can contribute to more targeted allocation of clinical resources and potentially reduce unnecessary investigations or interventions. However, the evidence remains heterogeneous because improvements in predictive discrimination or diagnostic accuracy do not necessarily translate into improvements in mortality, complications, quality of life, or patient satisfaction. Consequently, patient outcomes should remain the primary endpoint when assessing the clinical value of AI rather than relying exclusively on measures such as accuracy, sensitivity, specificity, or area under the receiver operating characteristic curve.

The patient-centred benefits of AI must also be considered alongside accessibility and equity. AI-supported services may expand access to specialized interpretation in settings where specialist clinicians are scarce, including some low-resource environments. At the same time, expensive infrastructure, computing requirements, connectivity limitations, proprietary systems, and shortages of trained personnel may restrict access. WHO therefore emphasizes that AI should contribute to universal access rather than become another source of health inequality. The 2026 WHO guidance additionally highlights particular concerns regarding fairness, capacity-building, power imbalances, and inequities affecting low- and middle-income countries.

Patient safety and experience are similarly dependent on how AI is implemented. AI-generated recommendations can reduce delays and support clinicians, but incorrect predictions or misleading generated information can adversely affect clinical decisions. WHO specifically identifies the possibility of inaccurate, incomplete, or biased outputs and warns about automation bias, whereby users may place excessive confidence in AI-generated recommendations. The evidence therefore supports a patient-centred model in which AI serves as an additional source of information rather than an autonomous substitute for clinical judgement.

3.4.3 Healthcare Workforce and System-Level Benefits

At the workforce level, AI can reduce the burden associated with repetitive, data-intensive, and administrative activities. Clinicians, nurses, radiologists, laboratory professionals, and other healthcare workers increasingly interact with large quantities of clinical information. AI can assist with image classification, documentation, data extraction, patient monitoring, scheduling, risk stratification, and summarization of medical records. In particular, generative and multimodal AI systems have been identified as potentially useful for clerical and administrative activities, including documentation and summarization of clinical encounters. For radiologists and laboratory professionals, AI-supported automation may facilitate preliminary screening and prioritization of high-volume examinations. Rather than eliminating professional roles, such applications may shift professional attention from repetitive recognition tasks toward complex interpretation, communication, quality assurance, and patient management. For nurses and other frontline professionals, predictive alerts and automated monitoring can potentially support earlier recognition of deterioration and improve prioritization of care. The overall finding is therefore more consistent with task transformation than simple workforce replacement.

At the organizational level, AI can contribute to improved allocation of healthcare resources by identifying high-risk patients, prioritizing urgent cases, optimizing workflows, and supporting operational forecasting. AI-enabled systems can potentially connect diagnostic, laboratory, clinical, and administrative information to provide a more integrated view of healthcare delivery. The FDA notes that AI technologies can analyze large and complex datasets and generate information supporting disease detection, diagnosis, treatment, and other aspects of healthcare.

However, workforce benefits are not automatic. New AI systems can create additional responsibilities involving data monitoring, model maintenance, validation, cybersecurity, documentation, and interpretation of algorithmic outputs. Healthcare professionals may also require new competencies in AI literacy and critical appraisal. Consequently, organizational benefits are greatest when implementation is accompanied by appropriate training, clearly defined professional responsibilities, effective workflow integration, and mechanisms for identifying and reporting algorithmic failures.

3.5 Challenges, Risks, and Future Directions

3.5.1 Data Quality, Bias, Privacy, and Security

Data quality emerged as one of the most important limitations affecting AI applications in healthcare. AI systems depend heavily on the quality, completeness, representativeness, and consistency of their training and operational data. Missing laboratory results, inconsistent clinical coding, incomplete electronic health records, measurement errors, changes in imaging protocols,

and differences in documentation practices can all influence model performance. A technically sophisticated algorithm trained on inadequate or unrepresentative data may therefore produce unreliable predictions when deployed in another clinical environment.

Algorithmic bias is closely connected to this problem. If training datasets underrepresent particular demographic, geographic, socioeconomic, or clinical populations, an AI system may perform differently across patient groups. WHO has specifically identified concerns that AI models can inherit or amplify biases associated with race, ethnicity, ancestry, sex, gender, and age. The problem is particularly important for global healthcare because datasets developed predominantly in high-income institutions may not adequately represent patients and healthcare environments in low- and middle-income countries (Narindrangkura, 2021). The 2026 WHO report explicitly identifies fairness, inequities, data colonialism, and capacity-building as issues requiring attention in AI-related health research.

Privacy and cybersecurity constitute additional risks because healthcare AI depends on highly sensitive personal information. Large-scale clinical datasets may contain identifiable demographic, genetic, diagnostic, and treatment information. Unauthorized access, inappropriate data sharing, insecure interfaces, or cyberattacks could therefore create consequences extending beyond technical system failure. WHO has emphasized that AI systems used in healthcare require safeguards for privacy, human rights, and data governance.

These findings demonstrate that improving algorithmic accuracy alone is insufficient. Responsible AI requires data governance throughout the data lifecycle, including appropriate collection, quality assessment, de-identification where appropriate, secure storage, controlled access, documentation of dataset provenance, and continuous monitoring for differential performance across patient groups. Bias assessment should similarly be treated as an ongoing process rather than a one-time evaluation during model development.

3.5.2 Explainability, Clinical Validation, and Human Oversight

The interpretability of complex AI models remains a major challenge in healthcare, particularly when deep-learning systems produce predictions through computational processes that clinicians cannot easily understand. A model may generate a highly accurate prediction without clearly indicating which clinical characteristics, laboratory values, imaging features, genomic factors, or physiological patterns contributed to the result. In high-stakes settings, this lack of transparency can reduce clinician trust, complicate error investigation, and make it difficult to communicate the basis and limitations of AI-supported recommendations to patients. Explainability is particularly important for AI applications in precision medicine, healthcare intelligence, personalized cancer treatment, and mental-health detection. These systems may support risk assessment, diagnosis, treatment selection, and patient monitoring, but their recommendations should remain clinically interpretable and subject to professional review (Hasan et al., 2026; Alam et al., 2025; Sami et al., 2026; Ayrin et al., 2025). Future research should assess not only whether explanations can be generated, but whether clinicians find them understandable, accurate, stable, and useful for real clinical decisions.

Clinical validation is therefore essential. Evidence from retrospective datasets or controlled research environments does not necessarily demonstrate that an AI system will perform reliably across hospitals, patient populations, equipment, clinical practices, or geographic regions. Differences in disease prevalence, patient demographics, clinical-record quality, laboratory procedures, imaging equipment, and local workflows may substantially influence model performance after deployment. Research on health informatics and public-health analytics similarly indicates that data quality, equity, and institutional context can affect whether AI-supported systems produce meaningful benefits in real healthcare settings (Hemal et al., 2025; Rahman et al., 2025).

External validation should include independent datasets, multiple healthcare institutions, diverse patient populations, and clinically meaningful outcomes. Prospective multicentre studies and pragmatic clinical trials are needed to determine whether AI improves patient outcomes, reduces diagnostic or treatment errors, saves clinician time, or improves resource use under routine conditions. This principle is consistent with broader work in AI-supported agriculture, where robust and explainable crop-recommendation systems must be tested under varied environmental and production conditions rather than evaluated only on a single dataset (Alam et al., 2024; Alam et al., 2026; Alam et al., 2023).

Human oversight remains central to safe implementation. AI should provide relevant evidence and decision support while allowing qualified healthcare professionals to assess uncertainty, identify possible errors, and override inappropriate recommendations. The role of human review is especially important where systems rely on large-scale or continuously updated data, because model outputs may change as data distributions, clinical practices, or patient populations evolve (Hossain et al., 2026; Sami et al., 2024). Clinical governance should clearly define who reviews AI outputs, when human confirmation is required, how disagreements between clinicians and algorithms are managed, and how errors are documented, reported, and investigated.

Lessons from other safety-critical fields reinforce this requirement. Fire-protection research demonstrates that modelling, early-warning systems, and predictive algorithms must be connected to physical knowledge, operational conditions, and safety procedures rather than used as isolated automated tools (Hossain, 2021, 2022; Hossain et al., 2023; Hossain & Alasa, 2024a, 2024b; Hossain et al., 2024; Hossain, 2025). Similarly, cybersecurity threat detection requires continuous monitoring because prediction errors or delayed responses can have serious consequences (Kaur et al., 2025). In healthcare, these lessons support a lifecycle approach in which explainability, validation, monitoring, accountability, and human oversight are treated as interconnected requirements.

3.5.3 Implementation Barriers and Future Research Priorities

Despite rapid technological development, AI implementation in healthcare remains constrained by organizational, technical, financial, regulatory, and professional barriers. Healthcare organizations may lack interoperable information systems, standardized and sufficiently diverse datasets, computing infrastructure, cybersecurity capacity, and personnel with both clinical and AI expertise. Smaller hospitals and resource-limited health systems may face particular challenges because implementation requires investment not only in AI software but also in data infrastructure, training, integration, validation, maintenance, and post-deployment monitoring. Interoperability is a major concern. AI systems that cannot communicate effectively with electronic health records, laboratory systems, imaging platforms, monitoring devices, and other clinical technologies may create fragmented workflows rather than effective decision support. Future research should examine standards-based integration of imaging, laboratory, genomic, physiological, and clinical-record data into validated multimodal systems. The broader growth of connected systems and IoT technologies illustrates both the potential and the technical complexity of integrating heterogeneous real-time data sources (Habib et al., 2024; Das et al., 2025).

Privacy, cybersecurity, and data governance are additional barriers. Healthcare AI often relies on highly sensitive personal and clinical data, requiring clear procedures for access control, secure storage, data sharing, model updating, and accountability. Research on scalable decision-making infrastructure highlights the importance of governance frameworks that support reliable analytics while protecting data quality and institutional responsibility (Sami et al., 2024). Future work should assess how privacy-preserving and secure data-management strategies influence model performance, fairness, cost, and practical usability. Regulatory uncertainty is also challenging because AI systems may change after deployment, particularly if they incorporate new data or are updated to address changing clinical needs. Future governance approaches should address initial validation as well as ongoing performance monitoring, model drift, cybersecurity, transparency, and accountability. This is particularly important when AI is used to influence diagnosis, treatment, or resource allocation.

Several research priorities emerge from this synthesis. First, researchers should conduct prospective multicentre studies and pragmatic trials to evaluate whether AI produces measurable improvements in patient outcomes rather than only strong technical performance. Second, datasets should better represent different ages, sexes, ethnic and socioeconomic groups, disease profiles, healthcare systems, and geographical settings. Third, future studies should strengthen multimodal and interoperable AI systems that combine complementary clinical information without increasing documentation burden. Fourth, responsible-AI research should examine fairness, privacy, cybersecurity, explainability, accountability, and continuous monitoring together rather than as separate concerns. The need for this integrated approach is visible across AI applications in e-commerce, business innovation, public health, agriculture, industrial safety, and healthcare (Sarwer et al., 2022; Alasa et al., 2025b; Hemal et al., 2025). Finally, research should investigate human–AI collaboration, including how clinicians interpret algorithmic outputs, when clinician override is most effective, how AI affects workload and professional judgment, and how trust should be calibrated to the reliability of a system.

AI-supported healthcare should also remain connected to established biomedical and experimental evidence. Research on biotechnology, pharmaceutical development, disease surveillance, Parkinson's disease, antimicrobial activity, and fungal research demonstrates that computational predictions require biological, clinical, and experimental confirmation before they can support high-consequence decisions (Tanvir et al., 2020; Rahman et al., 2022; Tanvir et al., 2024; Bulbul et al., 2019). This principle is equally relevant to emerging AI applications in industrial processes and safety systems, including hydrogen-related technologies, where predictive outputs must be validated within their operational context (Alasa et al., 2025a).

4. Conclusion

This systematic review demonstrates that artificial intelligence (AI) is increasingly transforming healthcare through applications in diagnostic accuracy, clinical prediction, and decision support. Across the reviewed evidence, AI technologies, particularly machine learning and deep learning, have shown potential to improve the interpretation of medical images, support early disease detection, predict clinical outcomes and risks, and assist healthcare professionals in making timely and evidence-informed decisions. These applications can enhance efficiency, reduce diagnostic and operational delays, and contribute to more

personalized and patient-centred care. However, the clinical value of AI depends not only on algorithmic performance but also on the quality and representativeness of data, external validation, interpretability, interoperability, cybersecurity, ethical governance, and effective integration into existing clinical workflows. Concerns regarding bias, privacy, transparency, accountability, and unequal access remain important barriers to responsible implementation. Overall, the evidence indicates that AI should function as a complementary tool that augments rather than replaces clinical expertise, with successful adoption requiring rigorous validation, continuous monitoring, multidisciplinary collaboration, appropriate regulation, and sustained investment in digital health infrastructure and professional training. Future research should therefore prioritize real-world clinical evaluation, diverse and representative datasets, explainable and trustworthy AI, and longitudinal assessments of patient outcomes to ensure that technological advances translate into safe, equitable, and clinically meaningful improvements in healthcare.

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References

- [1] Abayomi O, Adeola O, Adegbola O O, Ayotunde O and Odunayo O. (2024) The role of Artificial Intelligence in enhancing privacy protection for U.S. Citizens. *World Journal of Advanced Research and Reviews*, 2024, 23(2), 2922-2934. Article DOI: <https://doi.org/10.30574/wjarr.2024.23.2.2370>
- [2] Alam, M. I., Hemal, M. A. K. P., Sami, M. A., & Rahman, M. L. (2024). Robust and interpretable crop recommendation. *European Journal of Ecology, Biology and Agriculture*, 1(5), 168–184. <https://doi.org/10.59324/ejeba.2024.1%285%29.14>.
- [3] Alam, M. I., Sami, M. A., Al Masud, A., Ahmed, H., & Hossain, F. (2025). AI-driven big data analytics for personalized cancer treatment. *Journal of Computer Science and Technology Studies*, 7(11), 428–441. <https://doi.org/10.32996/jcsts.2025.7.11.40>.
- [4] Alam, M. I., Sami, M. A., Hemal, M. A. K. P., & Rahman, M. L. (2023). Predictive analytics and decision intelligence for climate-resilient agritech systems, 2(1), 44–56. <https://doi.org/10.32996/agjcs.2023.2.1.4>.
- [5] Alam, M. I., Sikder, T. R., Sami, M. A., Rahman, M. L., et al. (2026). A robust and explainable approach to crop recommendation. *Journal of Environmental and Agricultural Studies*, 7(3), 1–15. <https://doi.org/10.32996/jeas.2026.7.3.1>.
- [6] Alasa, D. K., Hossain, D., Jiyane, G., Sarwer, M. H., & Saha, T. R. (2025b). AI-Driven Personalization in E-Commerce: The Case of Amazon and Shopify's Impact on Consumer Behavior. *Voice of the Publisher*, 11(1), 104-116. <https://doi.org/10.4236/vp.2025.111009>
- [7] Alasa, D.K., Hossain, D., Jiyane, G. (2025a). Hydrogen Economy in GTL: Exploring the role of hydrogen-rich GTL processes in advancing a hydrogen-based economy. *International Journal of Communication Networks and Information Security (IJCNIS)*, 17(1), 81–91. Retrieved from <https://www.ijcnis.org/index.php/ijcnis/article/view/8021>
- [8] Almadani, B., Kaisar, H., Thoker, I. R., & Aliyu, F. (2025). A systematic survey of distributed decision support systems in healthcare. *Systems*, 13(3), 157.
- [9] Al-Nafjan, A., Aljuhani, A., Alshebel, A., Alharbi, A., & Alshehri, A. (2025). Artificial intelligence in predictive healthcare: A systematic review. *Journal of clinical medicine*, 14(19), 6752.
- [10] Ayrin, F. J., Rahman, M. M., Quader, M. A., Dass, A., Khondaker, M. M. H., & Chakraborty, M. (2025). MentalLLM: A transformer-based large language model framework for depression detection. In 2025 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE). <https://doi.org/10.1109/WIECON-ECE69386.2025.11525902>
- [11] Bulbul, I. J., Zahir, Z., Ahmed, T., & Alam, P. (2019). Comparative study of the antimicrobial, minimum inhibitory concentrations (MIC), cytotoxic and antioxidant activity of methanolic extract of different parts of *Phyllanthus acidus* (L.) Skeels (family: Euphorbiaceae). *World Journal of Pharmacy and Pharmaceutical Sciences*, 8(1), 12–57. <https://doi.org/10.20959/wjpps20191-10735>
- [12] Das, K., Tanvir, A., Rani, S., & Aminuzzaman, F. M. (2025). Revolutionizing agro-food waste management: Real-time solutions through IoT and big data integration. *Voice of the Publisher*, 11(1), 17–36. <https://doi.org/10.4236/vp.2025.111003>
- [13] Habib, M. R., Yusuf, M. A., Warnasuriya, W. M. H. N., Sunny, K., Rahaman, M. M., & Khan, M. R. K. (2024). A comprehensive review on the advancement of home automation system. In 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI) (pp. 638–642). IEEE. <https://doi.org/10.1109/ICoICI62503.2024.10696135>
- [14] Hasan, M. M., Alam, M. I., Chowdhury, M. A. H., & Anwar, M. M. (2026). AI-driven big data analytics for precision medicine and healthcare intelligence. *Frontiers in Computer Science and Artificial Intelligence*, 5(2), 41–62. <https://doi.org/10.32996/jcsts.2026.5.1.5>.
- [15] Hasan, S. U., Hasan, S., Shiwani, A., Kumar, S., Kumar, S., Nazeer, M. I., & Shiwani, S. (2025). A Systematic Review of AI-based Clinical Decision Support Systems: From Development and Implementation to Applications. *Pakistan Journal of Life & Social Sciences*, 23(1), 1482.
- [16] Hemal, M. A. K. P., Sayeed, N., Sami, M. A., Alam, M. I., Sikder, T. R., Dipa, S. A., & Rahman, M. L. (2025). Leveraging data analytics to strengthen public health and global economic sustainability. *European Journal of Medical and Health Research*, 3(4), 253–263. <https://doi.org/10.59324/ejmhr.2025.3%284%29.37>.
- [17] Hossain D., Alasa D.K, Jiyane G. (2023). Water-based fire suppression and structural fire protection: strategies for effective fire control. *International Journal of Communication Networks and Information Security (IJCNIS)*. 15(4):485-94. Available from: <https://ijcnis.org/index.php/ijcnis/article/view/7982>.

- [18] Hossain D., Alasa D.K. (2024a). Numerical modeling of fire growth and smoke propagation in enclosure. *Journal of Management World*. (5):186-96. <https://doi.org/10.53935/jomw.v2024i4.1051>.
- [19] Hossain D., Alasa D.K. (2024b). Fire detection in gas-to-liquids processing facilities: challenges and innovations in early warning systems. *International Journal of Biological, Physical and Chemical Studies*. 6(2):7-13. <https://doi.org/10.32996/ijbpcs.2024.6.2.2>.
- [20] Hossain, D. (2022). Fire dynamics and heat transfer: advances in flame spread analysis. *Open Access Res J Sci Technol*. 2022;6(2):70-5. <https://doi.org/10.53022/oarjst.2022.6.2.0061>.
- [21] Hossain, D. (2025). Water Efficient Suppression Material Fire Behaviour and AI Driven Safety in Future Fire Protection Research. *EJSMT*, 1(5), 62–76. [https://doi.org/10.59324/ejsmt.2025.1\(5\).07](https://doi.org/10.59324/ejsmt.2025.1(5).07)
- [22] Hossain, D.(2021). A fire protection life safety analysis of multipurpose building. Available from: https://digitalcommons.calpoly.edu/fpe_rpt/135/.
- [23] Hossain, D., Asrafuzzaman, M., Dash, S., & Rani, S. (2024). Multi-Scale Fire Dynamics Modeling: Integrating Predictive Algorithms for Synthetic Material Combustion in Compartment Fires. *Journal of Management World*. (5): 363-374.<https://doi.org/10.53935/jomw.v2024i4.1133>
- [24] Hossain, M. J., Bakhsh, M. M., Sami, M. A., Alam, M. I., Melon, M. M. H., & Manik, M. M. T. G. (2026). Self-adaptive artificial intelligence systems for large-scale data-driven decision making. In 2026 IEEE I3CTCON (pp. 1–8). <https://doi.org/10.1109/I3CTCON68242.2026.11507252>.
- [25] Kaur, J., Prabha, M., Samiun, M., Hasan, S. N., Hasan, R., Esa, H., et al. (2025). Comparative analysis of transformer and LSTM architectures for cybersecurity threat detection. *EAI Endorsed Transactions on AI and Robotics*, 4. <https://publications.eai.eu/index.php/airo/article/view/9759>.
- [26] Montani, S., & Striani, M. (2019). Artificial intelligence in clinical decision support: a focused literature survey. *Yearbook of medical informatics*, 28(01), 120-127.
- [27] Narindrarangkura, P., Kim, M. S., & Boren, S. A. (2021). A scoping review of artificial intelligence algorithms in clinical decision support systems for internal medicine subspecialties. *Aci Open*, 5(02), e67-e79.
- [28] Ogayemi, A. (2026). From obligation to enforcement: mapping EU AI act and CRA cybersecurity requirements to technical controls for LLM-based autonomous agents. *International Journal of Information Security*, 25(5), 164.
- [29] Ouanes, K., & Farhah, N. (2024). Effectiveness of artificial intelligence (AI) in clinical decision support systems and care delivery. *Journal of medical systems*, 48(1), 74.
- [30] Pasham, S. D. (2023). The function of artificial intelligence in healthcare: a systematic literature review. *International Journal of Acta Informatica*, 2(1), 32-42.
- [31] Rahman, M. M., Juie, B. J. A., Tisha, N. T., & Tanvir, A. (2022). Harnessing predictive analytics and machine learning in drug discovery, disease surveillance, and fungal research. *Eurasia Journal of Science and Technology*, 4(2), 28-35. <https://doi.org/10.61784/ejst3099>.
- [32] Rahman, M. M., Rahman, M. S., Islam, S., Khan, S. I., Ashik, A. A. M., Hossain, E., & Tanvir, A. (2025). Integrating data analytics into health informatics: Advancing equity, pharmaceutical outcomes, and public health decision-making. *Eurasian Journal of Medicine and Oncology*, 9(4), 284–295. <https://doi.org/10.36922/EJMO025300319>.
- [33] Rahman, M. M., Rahman, M. S., Islam, S., Khan, S. I., Ashik, A. A. M., Hossain, E., & Tanvir, A. (2025). Integrating data analytics into health informatics: Advancing equity, pharmaceutical outcomes, and public health decision-making. *Eurasian Journal of Medicine and Oncology*, 9(4), 284–295. <https://doi.org/10.36922/EJMO025300319>
- [34] Sami, M. A., Hemal, M. A. K. P., Alam, M. I., & Rahman, M. L. (2024). Data governance and analytics infrastructure for scalable decision-making. *European Journal of Applied Science, Engineering and Technology*, 2(2), 388–403. <https://doi.org/10.59324/ejaset.2024.2%282%29.28>.
- [35] Sami, M. A., Rahman, M. L., Tanni, Z. A., Munmun, Z. S., Nusrat, S., & Biswas, B. (2026). Artificial intelligence and big data for precision medicine. *Frontiers in Computer Science and Artificial Intelligence*, 5(6), 36–43. <https://doi.org/10.32996/fcsai.2026.5.6.7>.
- [36] Sarwer, M. H., Saha, T. R., & Hossain, D. (2022). Driving Business Innovation with Artificial Intelligence, Machine Learning and Blockchain Technology. *Journal of Business and Management Studies*, 4(3), 221-230. <https://doi.org/10.32996/jbms.2022.4.3.21>
- [37] Tanvir A, Jo J, Park SM. Targeting Glucose Metabolism: A Novel Therapeutic Approach for Parkinson's Disease. *Cells*. 2024 Nov 13;13(22):1876. doi: 10.3390/cells13221876. PMID: 39594624; PMCID: PMC11592965.
- [38] Tanvir, A., Juie, B. J. A., Tisha, N. T., & Rahman, M. M. (2020). Synergizing big data and biotechnology for innovation in healthcare, pharmaceutical development, and fungal research. *International Journal of Biological, Physical and Chemical Studies*, 2(2), 23–32. <https://doi.org/10.32996/ijbpcs.2020.2.2.4>
- [39] Tun, H. M., Rahman, H. A., Naing, L., & Malik, O. A. (2025). Trust in artificial intelligence–based clinical decision support systems among health care workers: systematic review. *Journal of Medical Internet Research*, 27, e69678.
- [40] Xu, Q., Xie, W., Liao, B., Hu, C., Qin, L., Yang, Z., ... & Luo, A. (2023). Interpretability of clinical decision support systems based on artificial intelligence from technological and medical perspective: a systematic review. *Journal of healthcare engineering*, 2023(1), 9919269.